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A METHOD FOR NON-PARAMETRIC DAMAGE DETECTION THROUGH THE USE OF NEURAL NETWORKS

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SUMMARY

A neural network-based approach is presented for the detection of changes in the characteristics of structure-unknown systems. The approach relies on the use of vibration measurements from a 'healthy' system to train a neural network for identification purposes. Subsequently, the trained network is fed comparable vibration measurements from the same structure under different episodes of response in order to monitor the health of the structure. The methodology is applied to actual data obtained from ambient vibration measurements on a steel building structure that was damaged under strong seismic motion during the Hyogo-Ken Nanbu Earthquake of 17 January 1995. The measurements were done before and after repairs to the damaged frame were made. A neural network is trained with data after the repairs, which represents 'healthy' condition of the building. The trained network, which is subsequently fed data before the repairs, successfully identified the difference between the damaged storey and the undamaged storey. Through this study, it is shown that the proposed approach has the potential of being a practical tool for a damage detection methodology applied to smart civil structures. © 1998 John Wiley & Sons, Ltd.

KEY WORDS: damage detection; health monitoring; non-destructive evaluation; system identification; neural network; ambient vibration; steel structures

1. INTRODUCTION

1.1. Background of damage detection

Damage detection is a challenging problem that is under vigorous investigation by numerous research groups using a variety of analytical and experimental techniques. Non-destrucive evaluation (NDE) methods for the detection of damage in structural systems have been receiving increasing attention in the recent past.[1]

Health monitoring techniques may be classified as global or local. Global methods attempt to simultaneously assess the condition of the whole structure, whereas local methods focus non-destructive evaluation (NDE) tools on specific structural components. However, the universe of damage detection scenarios likely to be encountered in realistic applications to all candidate physical systems is very broad and encompassing. Among the numerous considerations which influence the choice and effectiveness of a suitable health monitoring method are:

1. the variety of materials of construction,
2. the level of damage and deterioration of concern,

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3. the type of sensors used,
4. the nature of the instrumentation network,
5. the extent of available knowledge concerning the ambient dynamic environment,
6. the degree of measurement noise pollution,
7. the spatial resolution of the sensors,
8. the configuration and topology of the test structure,
9. the sophistication of available computing resources,
10. the complexity of the detection scheme,
11. the degree of a priori information about the condition of the structure,
12. the selected threshold level for detecting perturbations in the system condition,
13. the depth of knowledge concerning the failure modes of the structure, etc.

Among the promising NDE methods are those based on the analysis of structural dynamic response measurements to identify a suitable mathematical model corresponding to the (changing) state of the physical structure.

While there are many approaches that have been investigated or are still being developed for signature-based NDE of structures, the class of health-monitoring approaches that do not require detailed knowledge of the vulnerable parts of the structure, or of the failure modes of the structure, have a significant advantage in that they have the potential to cope with unforeseen failure patterns. Furthermore, health monitoring techniques that rely on non-parametric system identification approaches, in which *a priori* information about the nature of the model is not needed, have a significant advantage when dealing with real-world situations where the selection of a suitable class of parametric models to be used for identification purposes is quite often a demanding task.[2,3]

1.2. Previous work

The above listed issues have motivated many researchers to conduct studies in the field of health monitoring and damage detection. Noteworthy recent publications in this area are the works of Aktan *et al.*,[4] Beck *et al.*,[5] Doebling *et al.*,[6] Ghaboussi and Banan[7], Hjelmstad and Shin[8], Housner *et al.*,[9] Natke *et al.*,[10] Stubbs[11], Wen[12] and Yao and Yao.[13]

Among the structure-unknown identification approaches that have been receiving growing attention recently are neural networks. A study by Masri *et al.*[14] has demonstrated that neural networks are powerful tools for the identification of systems typically encountered in the structural dynamics field. Neural networks were originally developed to simulate the function of the human brain or neural system. Subsequently, they have been widely applied to diverse fields ranging from biology to many engineering fields.

The authors have developed a damage detection methodology based on the identification of a high-fidelity neural network.[15] In the previous work, the performance of the neural network-based damage detection methodology was explored by means of numerical simulation studies with linear as well as non-linear systems, with a wide range of parameter changes. By these studies, it was shown that the proposed approach was a robust method for detecting relatively small changes in the parameters of the underlying physical system, even with the presence of noise pollution in the monitored data.

1.3. Opportunity of Kobe earthquake

The Hyogo-ken Nanbu Earthquake hit one of the most densely populated urban areas of Japan in the early morning of 17 January 1995, resulting in a major disaster. The death toll from the earthquake exceeded 5500. More than 200 000 buildings and houses were totally or partially destroyed during the intense seismic motion and subsequent fire.[16,17]

The earthquake taught structural engineers some valuable lessons, while it also provided the authors with a unique opportunity to apply the previously presented damage detection methodology to actual physical data. Although there were no fully instrumented buildings among those heavily damaged during the

earthquake, there was an opportunity to carry out ambient vibration measurements at a damaged steel frame building. Since the building fortunately survived with only repairable structural damage, it furnished another opportunity to carry out measurements after the repairs, which made it possible to apply the method under consideration and to compare the results for the damaged and undamaged states.

1.4. Scope

This paper explores the potential of a time-domain, neural network-based identification procedure to detect structural changes through the application of the methodology to actual physical data obtained from a damaged building in the 1995 Kobe Earthquake. The methodology, which has been previously studied by means of numerical simulations, is demonstrated with actual physical data to demonstrate its potential as a practical damage detection approach.

Sections 2 and 3 describe the general characteristics of the building and explain the data processing scheme used, respectively. Section 4 provides preliminary observations of the measurements obtained through the use of conventional signal processing methods. Section 5 is the core part of this paper, in which the concept behind the proposed methodology is explained, and the results of its application are presented.

2. BUILDING CHARACTERISTICS

2.1. Description

The building is located in one of the most devastated areas near the centre of Kobe, that suffered from strong earthquake motion scaled at seismic intensity 7 by the Japan Meteorological Agency (JMA). The seismic intensity scale 7 is described as 'very disastrous' motions that involve demolition of houses by more than 30 per cent, intense landslides and large fissures in the ground. Figure 1 shows the location of the building and the area of the seismic intensity 7 in the earthquake.

The building was a seven-storey steel moment-resisting frame building, that has a floor plan of 11 m by 13 m and a total height of 23 m.

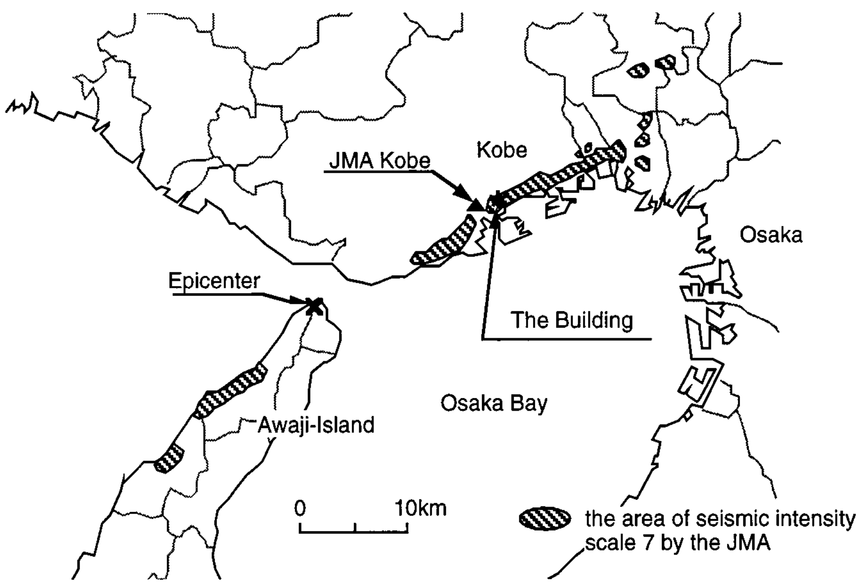

Figure 1. The location of the building and the area of the seismic intensity 7 in the earthquake

2.2. Sustained damage and repairs done

Several portions, mostly at the beam-column connections of the steel frame, suffered damage which manifested itself as yield cracks during the strong motion of the earthquake. The extent of the damage was discovered through post-earthquake inspections, which were carried out at all the beam column connections of the building after removing nonstructural interior elements and fireproof materials.

The middle storeys of the building, between the third-storey and the fifth-storey, were heavily damaged in the north–south direction, while the other storeys sustained only minor damage or no substantial structural damage. The damage induced in the middle storeys was typical of the damage phenomenon encountered in damaged buildings during the earthquake.

The damaged frame was repaired after the earthquake so as to restore the building structure to its original condition before the earthquake. Thus, the structure after the repairs can be regarded as recovering its structural integrity and the original dynamic properties, thus constituting the 'undamaged' state of the subject building.

2.3. Instrumentation

Ambient vibration measurements were conducted before and after the repairs to the damaged frame were made. The primary purpose of the measurements was to evaluate the effects of the repairs on the dynamic characteristics of the building.

The sensors, consisting exclusively of velocity transducers, were simultaneously located at every floor of the building so that the interstorey velocity, displacement and restoring force could be determined from the processed data.

The instrumentation was selected to directly measure velocity, as velocity sensors have the highest sensitivity in the frequency range of interest. The measurements were carefully done, making sure that there was a minimum amount of disturbing traffic vibration or wind.

3. DATA PROCESSING

3.1. Integration, differentiation and filtering of data

As the first step of data processing, the measured data were filtered by a low pass filter to eliminate measurement noise. Subsequently, the filtered data, which were originally measured as velocity signals, were converted into displacement and acceleration by integration and differentiation with respect to time, respectively. Figure 2 shows a typical example of the measured ambient vibrations, which are the time history of the acceleration, velocity and displacement at the fourth floor for a 30 s duration.

3.2. Interstorey vibration states

As previously described, the measurements were acquired simultaneously at each floor of the building so that the interstorey vibration states could be estimated from the measurements. The interstorey displacements and interstorey velocities were extracted by taking the difference of each measured data set between each two adjacent floors, in the time domain. The bottom two panels of Figure 3 are a typical example of interstorey displacement and interstorey velocity corresponding to the fourth storey.

3.3. Extracting restoring force from chain system response

The restoring force of each storey was determined by the method of Masri *et al.*,[2] Figure 4 shows the outline of the method in the case of base-excitation or free vibrations. Knowing the mass of each floor, which can be obtained from design information, the inertia force at each floor is estimated by multiplying the acceleration at a given floor by the mass of the floor. The interstorey restoring force is extracted by

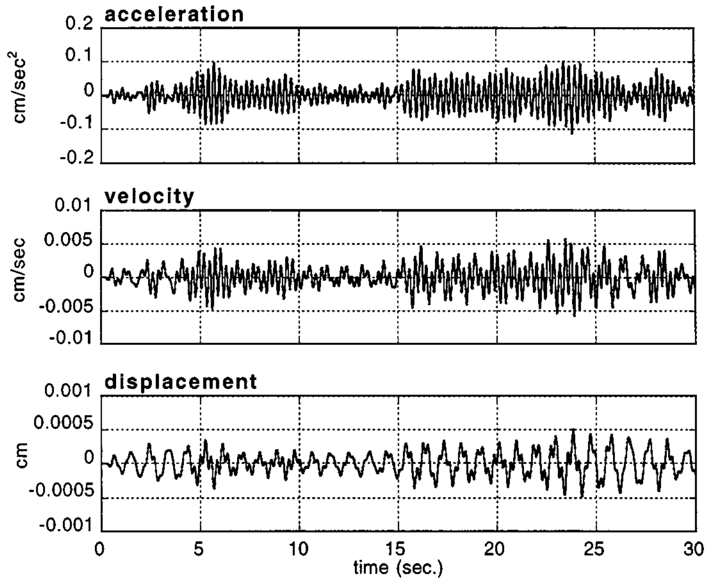

Figure 2. Typical example of measured ambient vibration at fourth floor

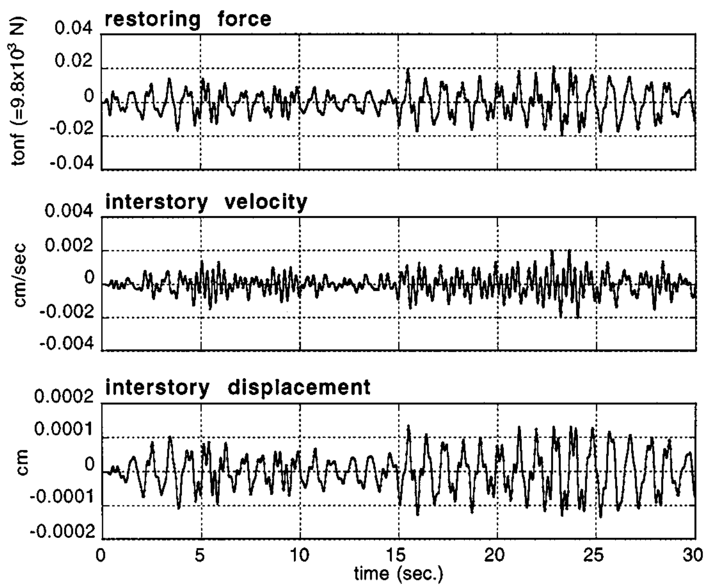

Figure 3. Typical example of interstorey displacement, interstorey velocity and restoring force at fourth storey

cumulatively summing up the inertia force at each floor from the top of the building down to the basement. The top panel of Figure 3 is a representative sample of the restoring force at the fourth storey.

These processed data for each storey were utilized in the application of the neural network damage detection approach which is described in Section 5.

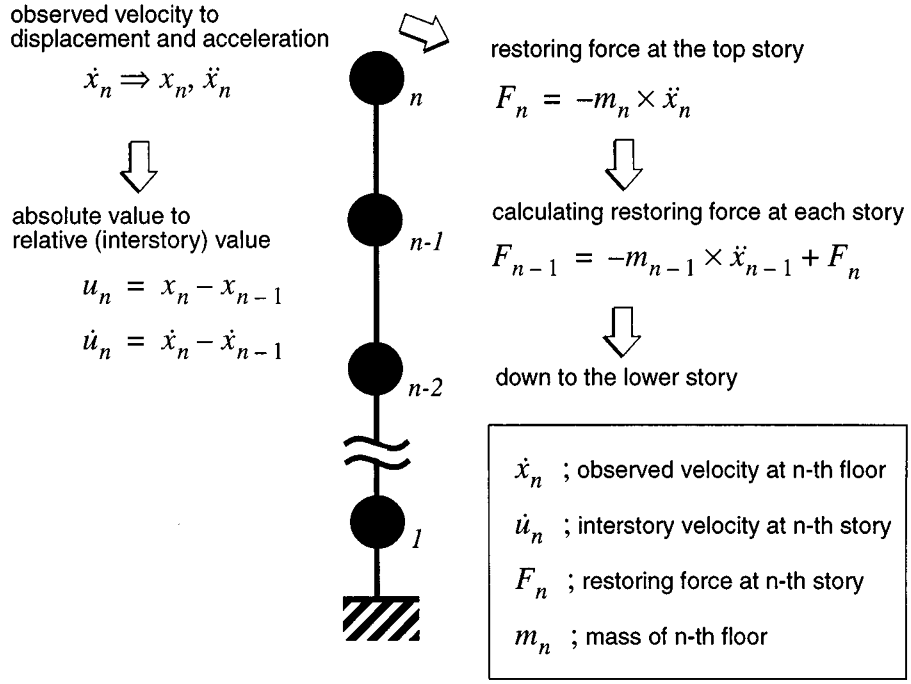

Figure 4. The outline of the process to extract interstorey vibration states assuming base-excitation or free vibrations

4. PRELIMINARY OBSERVATION OF THE DATA

4.1. Comparison of transfer function before and after repairs

Through a preliminary evaluation of the data obtained from the vibration measurements, the dynamic characteristics of the structure before and after the repairs were directly compared in the frequency domain. Figure 5 shows the transfer function between the basement and the rooftop of the building in the north–south direction, in which the structure suffered major damage. The upper panel shows the magnitude of the transfer function, while the lower panel shows the phase angle, both plotted versus the frequency. The dashed line indicates the transfer function before the repair (i.e. in the damaged state), while the solid line indicates the corresponding function after the repair (i.e. in the undamaged state).

The dominant peaks around 1.1 and 3.5 Hz in the figure correspond to the first and second natural frequencies, respectively. It can be seen that the first natural frequency shows an increase of about 7 per cent after the repair. The amount of the increase of the natural frequency corresponds to an increase of about 14 per cent in the overall stiffness, which can be attributed to the effects of the repair.

Although, the observation of the natural frequency of the repaired structure indicates that the repair effectively stiffens the structure, one cannot, solely on the basis of the results shown in Figure 5, specify which part, or which storey of the structure has been repaired. Similarly, one cannot determine which storey has been damaged only by observing the natural frequency of a structure. The approach of the authors resolves the problem by applying the damage detection methodology to the individual interstorey sub-systems of a given structure.

4.2. Comparison of phase-plane plots before and after repairs

Comparison of the phase-plane plots before and after the repairs provides a direct observation of the changes in the dynamic characteristics of a specific storey. A phase-plane plot is obtained by plotting the

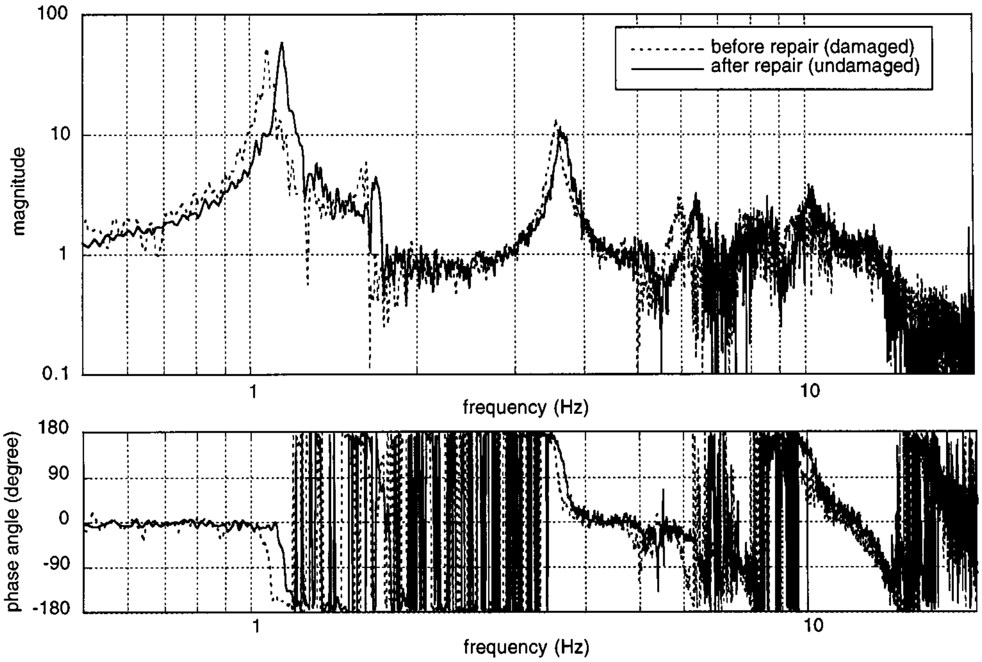

Figure 5. Comparison of transfer function before and after repairs

restoring force versus the interstorey displacement. Figure 6 shows an example of the comparison of phase-plane plots before and after repairs at the fourth storey and the first storey, which are typical examples of a damaged and an undamaged storey, respectively. The horizontal axis of the figures represents the interstorey displacement, and the vertical axis represents the restoring force. The interstorey displacement and the restoring force were extracted from the measurements through the data processing procedure explained in the previous section.

As shown in the figures, the phase-plane plots form slender ellipsoid-like figures which resemble the phase-plane diagrams of a damped single-degree-of-freedom oscillator. The angle made by the long axis of the 'ellipsoid' and the horizontal axis corresponds to the linear stiffness of the storey.

From the plot for undamaged storey (Figure 6(b)), it is seen that the stiffness before and after the repairs shows no significant change, except for their amplitude. On the other hand, the plot for the damaged storey (Figure 6(a)) shows that the stiffness after repairs is clearly larger than the stiffness before the repairs. This indicates that the stiffness has increased as a consequence of the repairs at the indicated storey. The difference in the magnitude of the measured data is attributed to the difference of the input level of ambient vibration and has nothing to do with the effect of the repair.

As shown above, the direct comparison of the phase-plane plots can be conveniently utilized for damage detection. However, the practical utilization of this approach requires a scheme to quantify the difference between two 'ellipsoids'. One way of accomplishing this is by using the author's non-parametric identification approach[2] in which the restoring force surface can be approximated by a surface expressed in terms of suitable basis functions related to the state variables (relative displacements and velocities) of the respective storey.

The neural network-based approach presented in the next section provides a fundamentally different, yet practical scheme to implement the damage detection methodology based on the observation of interstorey vibration states.

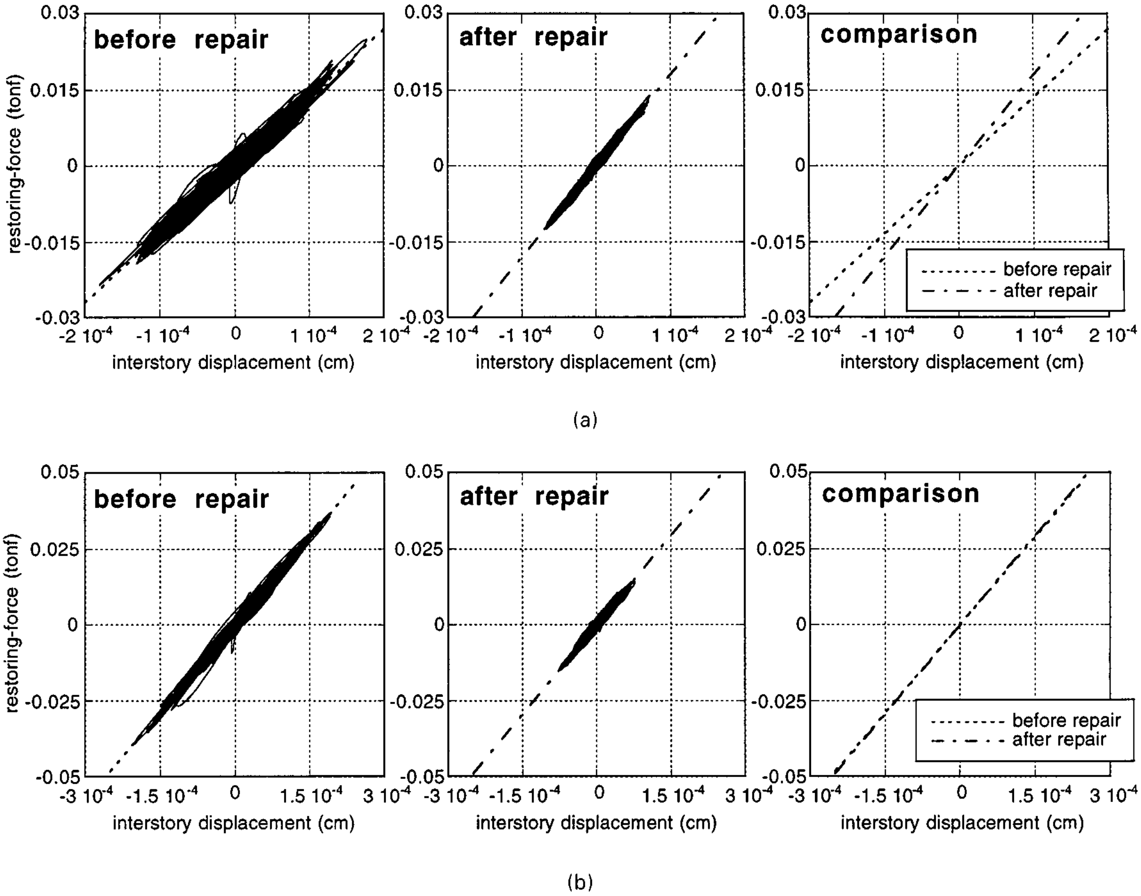

Figure 6. Comparison of phase-plane plots before and after repairs: (a) comparison at the fourth storey (damaged storey); (b) comparison at the first storey (undamaged storey)

5. NEURAL NETWORK APPROACH

5.1. Basic idea

Figure 7 shows the schematic diagram of the approach of this paper for the damage detection methodology using neural networks. The overall procedure is divided into two parts: (1) the training stage and (2) the detection stage.

In the training stage, as depicted in the left-hand side of the figure, a neural network is trained by the data obtained from the undamaged system using an appropriate training method. In the detection stage, as shown in the right-hand side of the figure, the trained network is fed input data, that is the same input to the system (reference structure). Then, the output from the network and the output from the system are compared to each other. If the network has been well trained, and if the system characteristics have not changed, both the system and the network will have matching outputs. On the other hand, if the system has changed, the output from the system will not correspond any more to the output of the trained network; consequently, the network will yield an output 'error'. Therefore, the deviation between the output from the system and the output from the network provides a quantitative measure of the changes in the physical system relative to its 'healthy' condition.

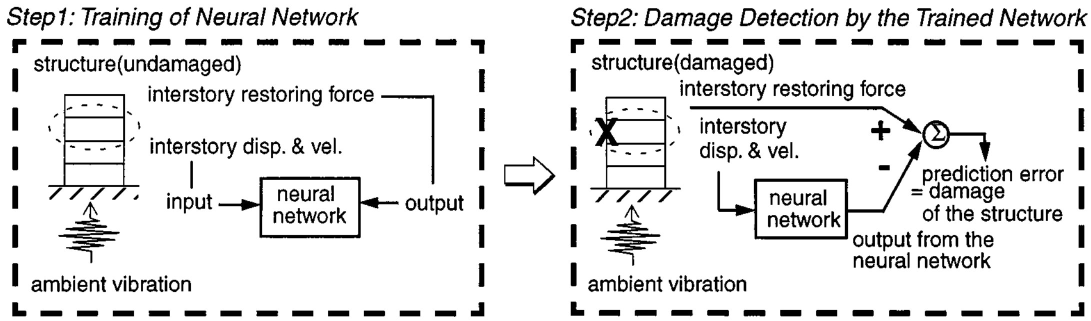

Figure 7. Schematic diagram of damage detection using neural networks

Note that the proposed methodology requires establishing a reference state of the structure (by training a suitable neural network only once) whenever the monitoring system is originally installed. From then on, continuous monitoring will be performed to track the network output error. This feature of the method is analogous to other structural health monitoring approaches based on vibration signature analysis.

Using this methodology, changes (damage) in the system may be detected just by observing the output error of the trained network. This simplicity of the procedure makes the scheme appealing for field implementation, provided an appropriately sensitive measure of the 'error' can be identified. Consequently, one of the main issues of interest is the quantification of the changes in the neural network output with respect to changes in the physical system parameters.

5.2. Neural network architecture

In this study, an individual network is prepared for each storey. Each network represents a physical system corresponding to a specific storey of the building. The training and detection are done for each individual storey using interstorey vibration states described in the previous section.

The diagram of the neural network used in this study is shown in Figure 8. The network is a feed-forward multilayer network which has two input nodes, two hidden layers and one output node. The first hidden layer has 15 nodes and the second layer has 10 nodes. The interstorey displacement and the interstorey velocity are selected as the input to the network. The restoring force is selected as the output of the network. Since the restoring force can be positive or negative, a bipolar sigmoid function defined as

$$f(t, \alpha) = \frac{1 - \exp(-\alpha t)}{1 + \exp(-\alpha t)}$$

is chosen as the activation function at each node, so that the output can have either positive or negative sign.

The network architecture was designed based on the previous work by the authors.[14,15] The architecture of such a network which is capable of providing a high-fidelity representation of a broad class of linear as well as non-linear systems, without any modification, is available in the work of Masri *et al.*[14]

5.3. Training of the neural networks

The method of approach requires the use of vibration measurements from a 'healthy' system to train a neural network for identification purposes. In this study, data from each story after the repairs, which represent 'healthy' condition of the building, were used to train a neural network for each storey.

The influence of the length of training data set and the effect of additive noise are discussed in the previous work by the authors.[15]

The training of the neural network was accomplished by using the adaptive random search method. This method was developed as an efficient global optimization algorithm.[18] The adaptive random search method

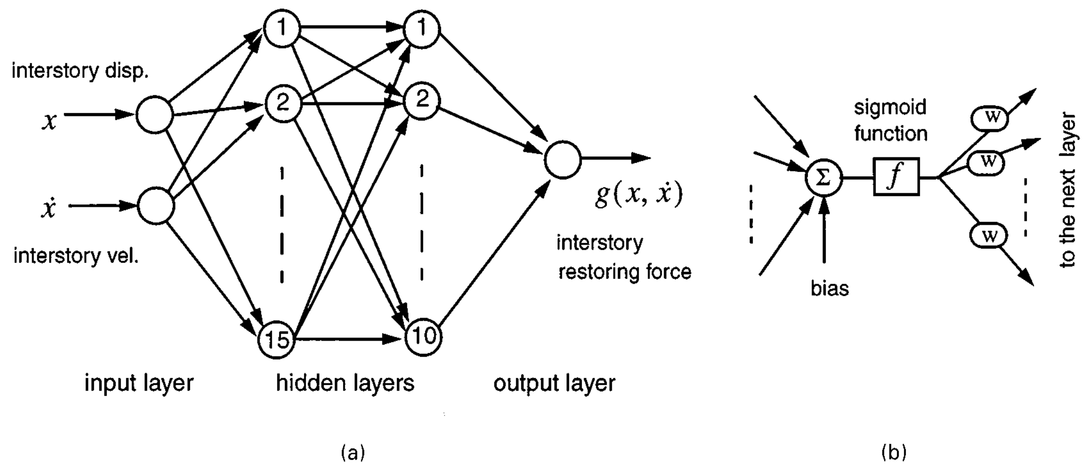

Figure 8. Feedforward multilayer neural network: (a) network architecture; (b) connections at a typical node

significantly improves the convergence rate of the minimizer of a given cost function. In conventional random search approaches in optimization problems, slow convergence rates hinder practical applications, especially when the order of the parameter vector is high. In the adaptive random search method, the variance of the step-size distribution is periodically optimized, thus resulting in a much improved convergence rate.

One of the advantages of using random search approached is that the search sequence will not be trapped at a local minimum. Although backpropagation training methods, which are commonly used to train feedforward networks, are, in general, faster than random search methods, backpropagation methods quite often get trapped at local minima instead of converging to the global minimum, thus providing an inaccurate representation of the underlying system being identified.

5.4. Detection results

The trained networks were subsequently fed data before the repairs, which represent the damaged condition for each storey. Then, the output error for each network was determined.

Typical results for a damaged and an undamaged storey are shown in the Figures 9 and 10, respectively. Figure 9 shows the results for the fourth storey, which had cracks at several beam column joints, while Figure 10 shows the results for the first storey of the building, which did not suffer any structural damage. The left column of each figure is the results of the data after repairs, which essentially represents the 'healthy' condition before damage. The right column of each figure provides corresponding results for the data before repairs, which represents conditions after the occurrence of damage. The top panels of each figure show the restoring force of the storey obtained from the measurements; the middle panels of each figure show the output of the neural networks, and the bottom panels show the differences between the actual restoring force and the output from the neural networks, which are expected to indicate the inherent damage level. For ease of comparison, identical scales are used for each panel of plots.

By comparing the left bottom panels (Figure 9(a) and 10(a)) between the fourth and first storey, it is seen that both networks yield a fairly small output error signal, which indicates that the networks were well trained to represent the structural characteristics before damage. By comparing the right bottom panels (Figure 9(b) and 10(b)) between the same storyes, the network for the undamaged case 'after the quake' yields an output error of almost the same level, as shown in the Figure 10(a). On the other hand, the output error of the network for the damaged storey case 'after the quake' (Figure 9(b)) becomes significantly larger than the

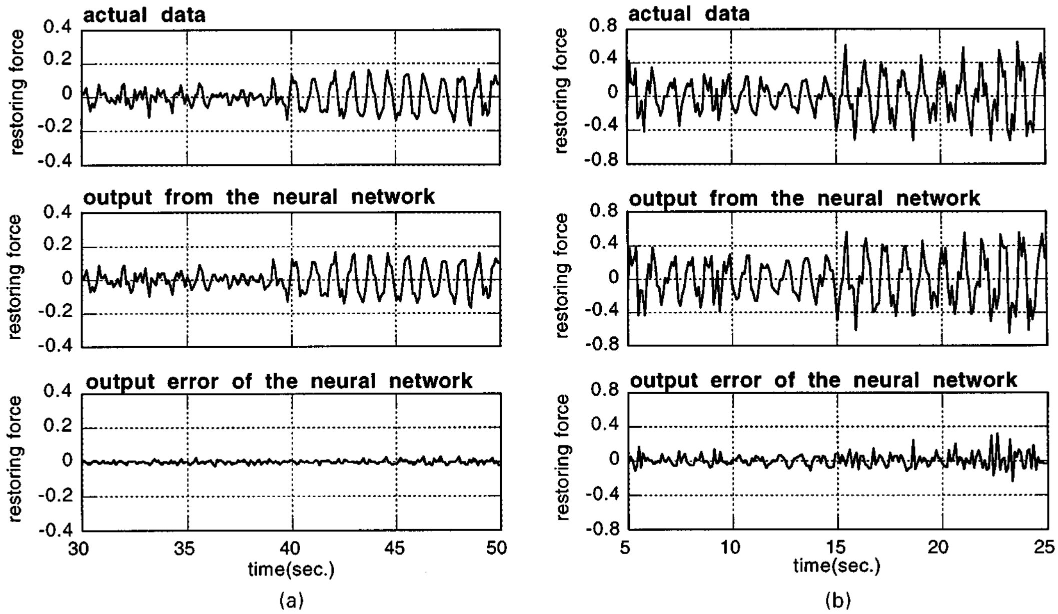

Figure 9. Typical results of detection for damaged storey (fourth floor): (a) before damage; (b) after damage

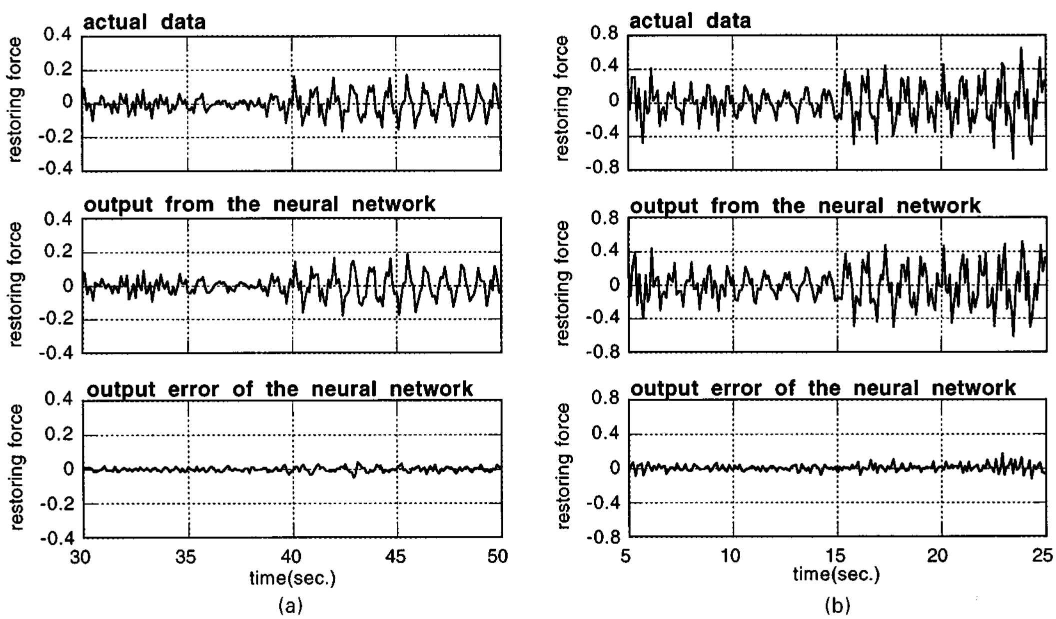

Figure 10. Typical results of detection for undamaged storey (first floor) : (a) before damage; (b) after damage

corresponding one shown in the Figure 9(a). This indicates that the neural networks trained by the data 'before the quake' have successfully identified the difference between the damaged and undamaged storeys.

6. DISCUSSION

6.1. Sensitivity of detection

To investigate and verify the sensitivity of the presented detection methodology, the root mean square (rms) errors are evaluated for several storeys to compare the results obtained between the damaged and the undamaged cases. The results are shown in Figure 11. This figure shows the output rms error of the networks for typical storeys of the building: the two damaged and two undamaged storeys. The left two panels of the figure are for the undamaged storeys and the right two panels are for the damaged storeys. The gray bars indicate the rms error 'before' the quake and black bars indicate those 'after' the quake. The numerical values of the figure are also shown in Table I.

Comparing the difference in conditions before and after the quake, it is clear that the rms error associated with the undamaged storey shows relatively small difference, while the rms error associated with the damaged storey becomes fairly large after the quake. Especially at the fourth storey, which suffered the heaviest damage during the quake, the rms error after the quake becomes twice as much as the error before the quake.

The storey stiffness of each storey were estimated through least-squares methods applied to the phase-plane plots of the restoring force, which are explained in Section 4.2. The results are shown in the last column of Table I. As shown in the table, those of damaged storeys decrease by more than 20 per cent of the virgin condition, while those of the first and the second storeys were changed by less than 7 per cent. Note that the degree of stiffness decrease corresponds fairly well to the change of the output rms error ratio of the neural networks. This indicates that the networks are capable of clearly identifying the damage level of more than 20 per cent decrease of the stiffness.

The above comparison also indicates the high sensitivity of neural network-based detection schemes. For example, in the comparison at the third floor, the stiffness of the storey is estimated to be degraded by 19 per cent, which is equivalent to 10 per cent decrease of the natural frequency. On the other hand, the neural network indicated as 45 per cent increase in the output error. This demonstrates the higher sensitivity of the proposed approach compared to ordinary frequency domain detection schemes.

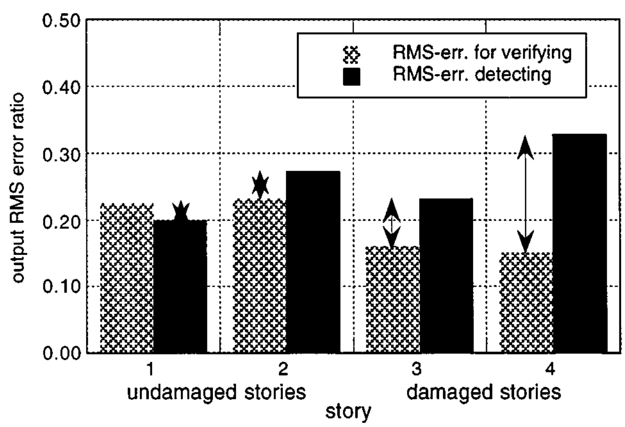

Figure 11. The comparison of rms error between undamaged and damaged storyes

Table I

Storey number	Undamaged rms error	Damaged rms error	Percentage change in rms error from undamaged case	Percentage change in stiffness from undamaged case†
1	0·224	0·199	− 11	− 1
2	0·232	0·273	+ 18	− 7
3	0·160	0·232	+ 45	− 19
4	0·150	0·328	+ 119	− 25

† Extracted from the restoring force characteristics (phase-plane plots) through least-squares methods

6.2. Training strategy

In Figure 11, observing the rms error of each storey for the undamaged case, note that all networks after training provide an rms error around 0·20, which is much larger than those of numerical simulations in the previous work by the authors.[15] In the subject numerical simulation, the network can be trained so as to yield rms error as small as 0·02. The larger rms error in this study is caused primarily by noise in the measurements, in addition to uncertainties in the building parameters used to extract the time history of the restoring forces. However, in spite of the larger rms error in the training stage, the network is still capable of detecting damage in the system on the order of 20 per cent degradation in the stiffness. In view of this, the modest level of rms error in the training stage is not a hindrance for detecting this level of damage.

6.3. Practical application

In a practical application, a threshold level may be set after the completion of the training, then the neural network-based detection system just observes whether the output error exceeds the threshold or not. Once the output error exceeds the threshold, the system alerts the residents of the building to possible damage of the structure. Note that these alert steps could be done automatically without any decision by human experts. This automatic detection and notification capability is quite useful for real-time health monitoring systems.

Neural networks may have practicability when implemented in hardware. Ordinary data processing schemes require a specific computer program, while neural networks are expected to be implemented in an LSI chip in the very near future. This might lead to an additional advantage as far as cost competitiveness is concerned.

6.4. Limitation of the methodology

Due to its non-parametric nature, the approach under discussion cannot ascertain which specific component (i.e. which individual structural component of the many that contribute to the overall resistance of a highly redundant storey) of the restoring force has changed and by what amount. Only changes in the global, composite measures are detectable. However, the utility of the methodology is not degraded by this limitation, since in virtually all physical structures damage manifests itself in the form of changes in the stiffness and/or damping associated with a cluster of structural members. As mentioned earlier, the primary concern for the proposed damage detection methodology is to detect and quantify the level of damage.

Note also that although it can even pinpoint the region of the structure where damage has occurred in the case of chain-like systems, there may be certain limitations of the methodology when applied to complicated structures or to systems with strong lateral-torsional coupling.

7. CONCLUSIONS

This study has explored a methodology based on using neural networks to detect structural changes in an existing building that was damaged in a severe earthquake which occurred in Kobe, Japan in 1995.

The approach is based on the identification of a high-fidelity neural network to match the restoring force associated with an element or substructure of the system to be monitored. By developing an accurate non-parametric representation of the system in its virgin (undamaged) state, the trained neural network can subsequently be used to furnish a reference restoring force which is compared to the corresponding time history of the system at a later stage during the monitoring process.

To show the practicability of the proposed methodology, it is applied to actual data obtained from ambient vibration measurements on a typical seven-storey steel building structure that was damaged under strong seismic motion. The trained networks, based on the presented methodology, successfully identified the difference between the damaged storey and undamaged storey.

Through this study, it is shown that the proposed approach has practical potential as a damage detection methodology applied to smart civil structures.

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